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"Density forecasts of inflation using Gaussian process regression models"

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Abstract

The present study uses Gaussian Process regression models for generating density forecasts of inflation within the New Keynesian Phillips curve (NKPC) framework. The NKPC is a structural model of inflation dynamics in which we include the output gap, inflation expectations, fuel world prices and money market interest rates as predictors. We estimate country-specific time series models for the 19 Euro Area (EA) countries. As opposed to other machine learning models, Gaussian Process regression allows estimating confidence intervals for the predictions. The performance of the proposed model is assessed in a one-step-ahead forecasting exercise. The results obtained point out the recent inflationary pressures and show the potential of Gaussian Process regression for forecasting purposes.

JEL Classification: C45, C51, C53, E31.

Keywords: Machine learning, Gaussian process regression, Time-series analysis, Economic forecasting, Inflation, New Keynesian Phillips curve.

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1. Introduction

Understanding the driving forces of inflation, as well as providing reasonably accurate inflation forecasts, have always been among the major topics of policy analysis. However, recent supply chain disruptions, the recovery in aggregate demand after the initial pandemic lockdowns around the world, and the fear of rising interest rates after a long period of cheap money, have increased inflation expectations and brought inflation to the sole spotlight of academic interest once again. After several decades of stable inflation, euro area (EA) countries have recorded an abrupt price boom in the last months. Moreover, the European Central Bank (ECB) has recently changed the declared definition of price stability (medium-term inflation below, but close to 2%). As of July 2021, the ECB defines its main policy goal as medium term inflation of exactly 2% [1]. The above described circumstances act as an ideal setup for an intensification of research efforts in inflation forecasting.

In parallel to the recent inflationary pressures, the methodological approach to time series forecasting is becoming more and more inclined to large, complex datasets and modern machine learning techniques. In recent years, several large-scale time series forecasting competitions have emerged, aiming to compare the accuracy of an array of novel machine learning (ML) techniques to conventional time series models [2–7]. These competitions were conducted on a wide set of economic time series of different frequencies, trending properties, seasonal patterns, etc. Although the choice of optimal forecasting model is extremely context-dependent, a common conclusion can be drawn that ML specifications typically outperform the classical econometric models. However, the literature on forecasting the EA inflation rate using ML techniques is very scarce.

This is exactly where we aim to contribute to the literature. We focus on forecasting inflation in 19 EA countries using Gaussian Process regression (GPR) and applying different sets of kernels. The main aim of this study is to provide researchers with a novel approach for modelling and predicting inflation rates within the New Keynesian Phillips Curve (NKPC) framework. The most important contribution of this paper is that the proposed GPR model generates not only a vector of predictions, but estimates confidence intervals, as opposed to other mainstream ML techniques. Additionally, to the best of our knowledge, this study provides a pioneering effort to use GPR for causal estimation within the NKPC, and to estimate confidence intervals of the obtained vectorial predictions. Finally, we considerably widen the geographical scope of previous ML-based inflation forecasting studies, focusing not only on the EA aggregate, but on all of its member states individually.

The remainder of the paper is structured as follows. Next section reviews the most recent literature on inflation forecasting and the Phillips curve. Section 3 presents the data. Section 4 describes the methodological approach as well as the design of the experiment. Empirical results are provided in Section 5. Finally, some concluding remarks are presented.

2. Literature Review

This section firstly provides a brief overview of literature related to the NKPC as the underlying theoretical model for the forecasting exercise presented in this paper. Secondly, we present the few ML contributions to inflation forecasting, and discuss the gaps in the literature that we aim to fill within this study.

2.1. Empirical testing of the NKPC

Ever since the seminal paper of [8], the hypothesized trade-off between unemployment and inflation has received attention from both policymakers and academics. In [9], the authors augmented the model further and developed the micro foundations of the so called NKPC:

$$\pi_t = \lambda \kappa x_t + \beta E_t\{\pi_{t+1}\}, \tag{1}$$

where π_t is the actual inflation rate, x_t is the output gap, κ is the output gap elasticity to marginal cost, $E_t\{\pi_{t+1}\}$ denotes inflation expectations, while λ and β are structural parameters.

Over time, the Phillips curve has become the workhorse model of monetary analysis and it has stimulated an entire branch of literature dealing with EA inflation. Even the ECB [10] has formally recognised the Phillips curve as representative for the EA inflation generating process. Depending on the selected model specification, choice of covariates, time period and the utilized methodology, the applicative value and forecasting accuracy of the Phillips curve in the EA context is quite heterogeneous. The empirical evidence found is mixed, there are studies where evidence is found in favour [11–13], while others find results against the original inflation-unemployment relationship [14]. Very similar context-dependent features are observed for the

EA NKPC specification, finding both confirmatory [15–17], and contrary evidence [18–20]. Despite all scepticism, the Phillips curve has stood the test of time and is still one of the most widely utilised macroeconomic models overall (see [21] and [22] for excellent surveys of related literature).

There is a wide debate in the literature over the right proxy variable for marginal cost in equation (1). The choice commonly comes down to the unit labour cost or output gap. As highlighted by [9], in the standard sticky price framework, output gap is proportional to the marginal cost. Moreover, Eurostat does not offer unit labour cost data in monthly frequency (analogous to inflation), so empirical studies of the NKPC mostly resort to output gap as a measure of economic slack [15,20,23]. In accordance with this empirical framework, GPR estimations in this paper are also based on the NKPC model given in equation (1), using output gap and inflation expectations as input data for inflation forecasts.

2.2. Recent ML advances in forecasting inflation

The advances over the past decade have proven the potential of ML techniques for time series forecasting [24–27]. Moreover, several extensive forecasting competitions have emerged, assessing the predictive accuracy of ML approaches in comparison to conventional time series modelling. For example, in [3], the authors utilise, *inter alia*, a rich set of different neural networks specifications and regression-based models, with the goal to forecast around a thousand different economic time series (the so called M3 forecasting competition). Their results show a dominance of multilayer perceptron and the Gaussian process regression. In [28], the authors analyse 111 time series (NN5 forecasting competition), obtaining the optimal forecasts via neural networks, Gaussian process regression estimates, and multiple regression models. On the other hand, in [4], the authors also assess the NN5 competition data, but they focus on comparing different strategies of input selection and forecast combinations. They find that Multiple-Output strategies (applied on seasonally adjusted data) perform significantly better than any other specification.

However, not many of these methods have been utilised to forecast the EA inflation rates. Apart from the Phillips curve-related papers covered in the previous section, the existing studies mostly trust conventional time series models such as VARs, ARIMA models and their extensions (e.g. [29]), factor models [30], or they follow the standard leading indicator approach [31]. To the best of our knowledge, there are only a few papers specifically tackling forecasting the EA inflation using ML techniques. Their contributions are briefly described as follows.

In [32], the authors present a pioneer utilization of then emerging class of neural network models. To be specific, they assess the feed-forward network with jump connections, using current and lagged values of inflation and unemployment as inputs to produce inflation forecasts for the US, Japan, and the EA. They apply "thick modelling", i.e. they combine forecasts of an ensemble of neural networks obtained with different starting values and different network architectures. The authors perform a set of goodness-of-fit assessments and diagnostic tools (both in sample and out of sample), finding that the obtained neural network forecasts are either comparable to the benchmark autoregressive processes, or they outperform them (depending on the analysed country, examined period, and the chosen inflation subcategory).

In [33], the authors provide another meticulous analysis of neural networks' performance when it comes to EA inflation forecasting. They asses as many as 540 different neural networks, differing in maximum number of iterations, learning rate, weighting schemes, and the number of hidden neurons; using lagged inflation, unit labour cost, nominal exchange rate, and monetary aggregate M3 as input variables. The obtained results speak in favour of Jordan neural networks over feed-forward ones (both in terms of forecasting accuracy and parsimony).

In [34], the authors compare the predictive accuracy of genetic algorithms and two other heuristic optimization methods, along with several dimension reduction techniques in an attempt to forecast the EA inflation rate. They apply the stated methods to an array of as many as 195 economic variables, finding that heuristic optimization techniques (sequential testing and a Bayesian model averaging approach in particular) outperform all other examined methods.

All three stated papers find ML-based inflation forecasting to be a promising field of research, so we aim to build upon their efforts even further. Acknowledging the dominance of Gaussian process regression in terms of predictive accuracy [3,28,35,36], we aim to provide the initial contribution of that sort to inflation forecasting. Our main contribution within this paper is presenting the mathematical foundations of GPR-based confidence intervals. Within this paper the stated methodology is utilized for inflation forecasting, but the applicative potential of this framework is much wider.

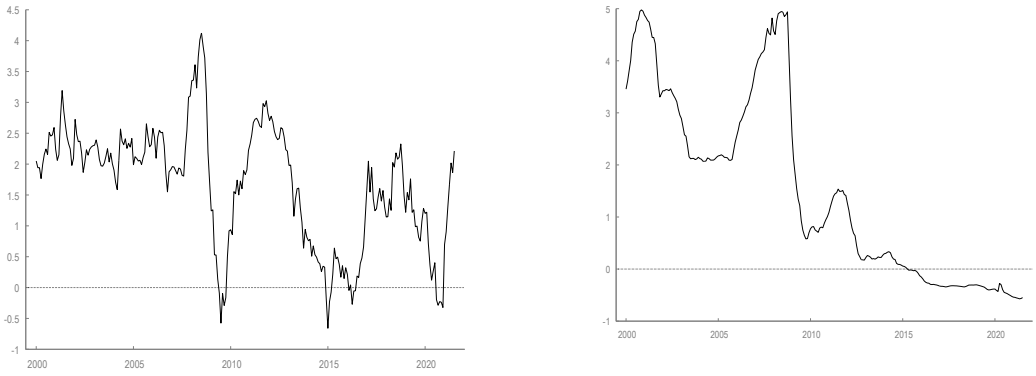
3. Data

In this study we aim to forecast monthly inflation data (year-on-year percentage changes obtained via the Harmonized Index of Consumer Prices) for the 19 EA countries, provided by Eurostat. See Figure 1 and Table 1. Our focal independent variables are output gap and inflation expectations, both stemming from the NKPC theoretical specification. Since π_t is of monthly frequency, this has conditioned our operationalization of independent variables. Output gap is obtained via the Hodrick-Prescott filter on the monthly industrial production index (provided by Eurostat), while inflation expectations are derived from the Joint Harmonised EU Consumer Survey conducted by the European Commission [37]. To be specific, we focus on question 6 from the consumer survey:

Q6. In comparison with the past 12 months, how do you expect consumer prices will develop in the next 12 months? They will: ++) Increase more rapidly, +) Increase at the same rate, =) Increase at a slower rate, −) Stay about the same, −−) Fall, N) Don't Know.

This question is asked on a regular monthly basis to consumers in each of the 19 EA member states assessed in this paper. There is a wide variety of quantification techniques that can be utilized to obtain an economy-wide numerical measure of inflation expectations. There is no consensus in the literature about the optimal quantification method and the results of these methods often heavily depend on the underlying (often non-realistic) assumption (see [38–40] for a discussion). Therefore, instead of arbitrarily choosing a particular method, we opt for utilizing a simple response balance[1] of question 6.

As additional control variables we use crude oil prices at the global market (in USD; accounting for cost-push inflation) and the EA 3-month money market interest rate as a monetary indicator (see Figure 1). The former variable is obtained from the US Energy Information Administration, while the latter is gathered from Eurostat.



(a) (b)

Figure 1. Inflation and interest rates in the EA (2000:01-2021:07) (**a**) Inflation; (**b**) Interest rates.

The entire dataset is seasonally adjusted (see e.g. [4,41] for a thorough exposition on the beneficial impact of seasonal adjustment on forecasting accuracy). The dataset spans at most from January 2000 to August 2021. Table 1 shows the descriptive statistics.

[1] A response balance (B) is the difference between the percentages of positive and negative responses to a particular survey question. In the case of Q6 from the consumer surveys, $B = (PP + 0{,}5P) - (0{,}5M + MM)$, where PP is the proportion of ++ replies, P is the percentage of + replies, MM is the percentage of $--$ replies, and M is the proportion of $-$ replies. It is a customary method for quantifying consumer survey results (European Commission, 2021) [37].

Table 1. Descriptive statistics (2000:01-2021:07).

Country		Inflation	Output gap	Expectations
Austria	mea	1.874	0.032	27.929
	SD	(0.805)	(3.969)	(8.544)
Belgium	mea	1.891	0.000	17.060
	SD	(1.183)	(4.044)	(10.577)
Cyprus	mea	1.595	0.000	11.567
	SD	(1.964)	(4.773)	(26.142)
Estonia	mea	3.262	0.037	32.992
	SD	(2.695)	(4.727)	(21.629)
Finland	mea	1.601	0.063	28.715
	SD	(1.121)	(4.317)	(13.953)
France	mea	1.524	0.035	17.773
	SD	(0.881)	(3.926)	(9.865)
Germany	mea	1.493	0.033	32.495
	SD	(0.824)	(4.468)	(11.930)
Greece	mea	1.778	0.000	17.560
	SD	(2.063)	(3.402)	(18.076)
Ireland	mea	1.553	–	24.470
	SD	(1.977)	–	(14.267)
Italy	mea	1.689	0.038	-0.632
	SD	(1.149)	(5.466)	(13.921)
Latvia	mea	3.423	0.000	26.649
	SD	(3.955)	(3.831)	(20.518)
Lithuania	mea	2.385	-0.023	43.166
	SD	(2.762)	(4.106)	(13.923)
Luxemburg	mea	2.162	0.000	16.326
	SD	(1.481)	(4.816)	(12.218)
Malta	mea	1.953	0.000	22.380
	SD	(1.241)	(5.226)	(19.984)
Nether-	mea	1.857	0.000	20.307
	SD	(1.230)	(3.159)	(17.178)
Portugal	mea	1.766	0.000	22.612
	SD	(1.526)	(4.124)	(15.073)
Slovakia	mea	3.311	0.000	35.424
	SD	(3.230)	(4.975)	(18.378)
Slovenia	mea	2.936	0.034	39.627
	SD	(2.811)	(4.508)	(14.333)
Spain	mea	1.981	0.021	9.071
	SD	(1.622)	(5.075)	(14.306)
EA	mea	1.673	-0.006	18.759
	SD	(0.963)	(3.193)	(9.546)

Note: SD denotes standard deviation. SD values in parentheses.

4. Methods

GPR was originally devised for interpolation. The works by [42–44] have been key in the development of GPR models. By expressing the model in a Bayesian framework, the authors extend GPR applications beyond spatial interpolation to regression problems. GPR models are supervised learning methods based on a generalized linear regression that locally estimates forecasts by the combination of values in a kernel [45]. Thus, GPR models can be regarded as a non-parametric tool for regression in high dimensional spaces. GPR models present one fundamental advantage over other ML techniques: they provide full probabilistic predictive distributions, including estimations of the uncertainty of the predictions. These features make GPR an ideal tool for forecasting purposes.

4.1. Definition of a Gaussian Process

A Gaussian Process (GP) is a stochastic process in which we have a random distribution over a space of functions that we will denote as f(x)[2]. This distribution over the function space f(x), with $\mathrm{x} \in \mathbb{R}^{\mathrm{d}}$ will be defined by a specific function that determines the mean value of the realizations, which we will denote as,

$$\mathrm{m}(\mathrm{x}) = \mathrm{E}(\mathrm{x}), \tag{2}$$

and a covariance function denoted as[3],

$$\mathrm{k}(\mathrm{x}, \mathrm{x}') = \mathrm{E}\big[\big(f(x) - m(x)\big)\big(f(x') - m(x')\big)\big] \tag{3}$$

The function f(x) is distributed as a GP, $f(x) \sim \mathcal{GP}\big(m(x), k(x, x')\big)$. Therefore, for a finite subset of observations $\{x_1 \dots x_n\}$, where $\mathrm{x_i} \in \mathbb{R}^{\mathrm{d}}$ the marginal distribution for this subset of observations is a multivariate Gaussian distribution,

$$f(X) \sim \mathcal{N}\big(m(X), k(X, X)\big), \tag{4}$$

defined by the mean vector, $m(X) = \big[\mathrm{m}(x_{1)}, \dots \mathrm{m}(x_n)\big]^{\mathrm{T}} \in \mathbb{R}^{\mathrm{n}}$; and the covariance matrix $k(X, X) \in \mathbb{R}^{\mathrm{nxn}}$ is a matrix defined in an analogous manner.

The covariance function k(x,x') allows the introduction of a priori information about the problem, i.e. a model of how the samples are related, or of the process that has generated them. Formally, the function K(x,x') defines the joint variance of the random variables associated with the GP, i.e. it models the covariance between (x,x'). This relationship or similarity between the two observations is specified by a kernel-like function (see for example [46])[4].

An alternative might be to model the fact that there might be a correlation between the input features that is certain directions which might have different variation. In order to model this anisotropy, one might use instead an inner product with a weighting matrix M that takes into account this fact, defining the dot product as[5],

$$\langle x, x' \rangle_{M} = x^{T} M x' \tag{5}$$

A natural weighting matrix is the inverse of the correlation matrix in the feature space, i.e., C_x^{-1}, so in this case the metric would be as follows:

$$\langle x, x' \rangle_{C_x^{-1}} = x^{T} C_x^{-1} x' \tag{6}$$

Another way to way to implement the metric is to construct a change of basis, on the axes of the weighting matrix M, understanding the new basis as a selection of either the eigenvectors of M or a rotated version of them. That is, the observation $\mathrm{x} \in \mathbb{R}^{\mathrm{d}}$ could be projected, by means of a transformation $\mathrm{U} \in \mathbb{R}^{\mathrm{dxk}}$, into a subspace of dimension k, that encompasses directions of interest for the task at hand.

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[2] The presentation and notation that we will follow is based on the texts of Williams and Rasmussen (2006) and MacKay (2003) [43,44].
[3] This covariance has the property of being positive definite. The covariance function will be defined for all possible combinations of input observations (x,x').
[4] The specification of a kernel allows the introduction of the functional form of dependence between the variables, the only limitation being that to be a valid covariance function it must generate positive definite matrices for sets of samples.
[5] Note that one source of confusion is to mistake the two types of correlation. The correlation K(x,x'), which indicates the similarity between two observations, corresponds to Gram's matrix, whereas for a natural weighting measure in the inner product, the covariance matrix of the observations X could be used to model the correlations between features.

This projection, for example, could be onto the eigenvectors associated with the highest eigenvalues of C_x , which would be the basis of Principal Component Analysis (PCA), or onto a basis such as the one provided by Factor Analysis (FA), with the appropriate rotation.

Since the change of basis can be understood as a preprocessing applied to the observations for each kernel, without changing the form of the kernel, in this work we will distinguish the kernel k(x,x') on the original space from the kernel that works with the data projected on a subspace of interest that we will denote as kp(x,x').

The regression analysis using GP incorporates a kernel function, which provides a similarity of the training data to each other and the similarity to the observations to be regressed on. We will compute a posterior distribution conditioned on the observations on which we want to perform the regression. The result will be that for each sample on which we calculate the regression we have a Gaussian distribution[6]. The prediction is the mean value of the distribution conditioned on the observation. Note that by having a distribution for each observation, confidence intervals can be calculated.

4.2. Process for making the prediction from the posterior distribution

One distinguishing feature of GP as opposed to other machine learning methods is that the model of the observations is done jointly (i.e. simultaneously) for the training and test samples. Note that we reserve a different part of the database for model validation, which enables the adjustment of kernel types and hyper parameters.

We create a partition of the database into two sets of size $\{n_1, n_2\}$, [(X1,Y1),(X2,Y2)], where (X1,Y1) are the n_1 training observations, and (X2,Y2) are the n_1 test observations. The inputs X2 will be used to create the model, i.e. the model will be created using only, [(X1,Y1),(X2,.)]. Therefore, the reference Y2 will not be used to estimate the model, but to validate the prediction.

Thus, for the regression over the new samples we create the function y2=f(X2), where f(.) is the mean value of the joint distribution for all test samples. In fact, the GP provide much more information, as provides the conditional distribution, p(y2|y1,X1,X2), which actually gives us how the response Y2 of the process is jointly distributed given the training observations (X1, Y1) and the inputs (X2,.) on which we want to make the prediction.

First, we will jointly model the probability distribution over the training and test outputs {Y1, Y2}, in the form of a Gaussian distribution as follows,

$$\begin{bmatrix}\mathbf{y}_1\\ \mathbf{y}_2\end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix}\mu_1\\ \mu_2\end{bmatrix}, \begin{bmatrix}\Sigma_{11} & \Sigma_{12}\\ \Sigma_{21} & \Sigma_{22}\end{bmatrix}\right) \tag{7}$$

Each component of the Gaussian distribution above being of the form: the vector of joint means will have two components μ_1 and μ_2 of size equal to the sample cardinality,

$$\begin{aligned}\mu_1 &= m(X_1) \in \mathbb{R}^{(n_1\times 1)}\\ \mu_2 &= m(X_2) \in \mathbb{R}^{(n_2\times 1)}\end{aligned} \tag{8}$$

The joint covariance matrix will consist of four components,

$$\begin{aligned}\Sigma_{11} &= k(X_1, X_1) \in \mathbb{R}^{(n_1\times n_1)}\\ \Sigma_{22} &= k(X_2, X_2) \in \mathbb{R}^{(n_2\times n_2)}\\ \Sigma_{12} &= k(X_1, X_2) \in \mathbb{R}^{(n_1\times n_2)}\end{aligned} \tag{9}$$

By the symmetry in the definition of the kernels we will have that the cross-covariance matrix satisfies that $\Sigma_{12} = \Sigma_{21}{}^T$. The prediction will be made from the conditional probability $p(\mathbf{y}_2 \mid \mathbf{y}_1, X_1, X_2)$ defined as follows:

$$p(\mathbf{y}_2 \mid \mathbf{y}_1, X_1, X_2) = \mathcal{N}(\mu_{2|1}, \Sigma_{2|1}) \tag{10}$$

[6] The prediction is the mean value of the distribution conditioned on the observation. Note that by having a distribution for each observation, confidence intervals can be calculated.

The mean of the distribution of the reference Y2, conditional on the training data, will depend on the cross-covariance between the training and test inputs, together with the covariance of the training inputs themselves, as follows:

$$\mu_{2|1} = \mu_2 + \Sigma_{21}\Sigma_{11}^{-1}(\mathbf{y}_1 - \mu_1) \tag{11}$$

Assuming we have de-meaned the process as part of the data preprocessing, i.e. we assume that global mean is, $\mu = 0$, the prediction is simplified as follows

$$\mu_{2|1} = \Sigma_{21}\Sigma_{11}^{-1}\mathbf{y}_1 \tag{12}$$

The covariance matrix of the test inputs conditional on the covariance of the train inputs, is estimated as follows

$$\Sigma_{2|1} = \Sigma_{22} - \Sigma_{21}\Sigma_{11}^{-1}\Sigma_{12} \tag{13}$$

By knowing the $p(\mathbf{y}_2 \mid \mathbf{y}_1, X_1, X_2)$ distribution, it is possible to make a point estimate using the, $\mu_{2|1}$, and/or it is possible to estimate in intervals, for example by providing the interval between the 5% and the 95% percentile, which would be obtained from the diagonal of the $\Sigma_{2|1}$ matrix.

A property of interest associated with point prediction $\mu_{2|1} = \Sigma_{21}\Sigma_{11}^{-1}\mathbf{y}_1$ is that the prediction consists of a linear combination of the training samples $\mathbf{y}_1$, weighted by the similarity between the test inputs and the training inputs, provided by the Σ_{21} matrix, discounting the autocorrelation of the input matrix, provided by the Σ_{11}^{-1}-factor.

4.3. Model fitting—Estimation of the hyper parameters

The distribution of the target values y_2 will depend on the marginal likelihood$p(y/X, \theta)$, which is a function of the θ parameters of the kernels, and on the mean function that we decide for our model.

The criterion for the estimation of the θ parameters of the GP will be the maximization of the marginal likelihood, i.e. selecting the vector of parameters θ for which the conditional probability of the target y with respect to the inputs X is maximum. That is, the estimate will be,

$$\hat{\theta} = argmax_{\,\theta} \quad \big(p(y/X, \theta)\big) \tag{14}$$

The marginal likelihood of the GP corresponds to a Gaussian distribution defined by functions parameterized by the input data, with mean $\mu_\theta = m_\theta(X)$ and variance defined by the kernel of the form $\Sigma_\theta = \mathrm{k}_\theta(\mathrm{X}, \mathrm{X})$, with d the dimensionality of the marginal and $|\Sigma_\theta|$ the determinant of the kernel matrix. The distribution is therefore of the form,

$$p(\mathbf{y}/X, \theta) = \frac{1}{\sqrt{(2\pi)^d |\Sigma_\theta|}} \mathrm{e}^{-\frac{1}{2}(y-\mu_\theta)^\top \Sigma_\theta^{-1}(y-\mu_\theta)} \tag{15}$$

The estimation is done on a logarithmic scale, which is equivalent to solving a quadratic form by maximizing the log marginal likelihood $\log p(\mathrm{y} \mid X, \theta)$ as follows:

$$\log p(\mathbf{y} \mid X, \theta) = -\frac{1}{2}(y - \mu_\theta)^\top \Sigma_\theta^{-1}(y - \mu_\theta) - \frac{1}{2}\log|\Sigma_\theta| - \frac{d}{2}\log 2\pi \tag{16}$$

The final criterion that we will follow will be to minimize the negative log marginal likelihood, defined as follows:

$$\hat{\theta} = argmax_\theta\big(p(y \mid X, \theta)\big) = argmin_\theta\,(-\log p(y \mid X, \theta)) \tag{17}$$

Since the usual kernels consist of differentiable functions with respect to the parameters that define them, the estimation of the parameters is usually carried out by means of gradient search. For more details see [44] and the GPy documentation [47].

4.4. Kernels

In this work we have implemented GPs based on combinations of various basic types of kernels. The reason is that a linear combination of kernels continues to be a kernel, and this allows us to model different aspects or properties of the series we work with.

The types of kernel that we have studied in this work are kernels that allow modeling the influence between samples with a different influence in terms of decay as a function of the distance between samples. We have considered the radial basis function that decays as the square of an exponential with the distance along with the Rational Quadratic Kernel decays in a hyperbolic way, that is, it has a greater radius of influence. On the other hand, we have also considered Matern-type covariance functions (3/2 and 5/2) and exponentials that have an influence between the two previous ones. Finally, we also consider the possibility of using a multilayer perceptron kernel, which has a saturation-type non-linearity that limits the area of influence and a periodic kernel to model the possible periodicities of the series studied.

The kernels mentioned above are isotropic, in the sense that they consider that distance does not provide privileged orientations. However, we will introduce in the distance measure a feature that allows us to model the dependence between the variables and therefore to model the fact that there are privileged orientations. In this case, the metric is defined as,

$$||x - x'||_M^2 = (x - x')^T M (x - x'), \tag{18}$$

where M determines the how the interactions between features are weighted. Note that in case of using M=I, the metric is the Euclidean distance.

The kernels used are, first of all, Radial Basis Function (RBF), the kernel is defined as follows,

$$k(x, x') = \sigma^2 e^{-\frac{\|x-x'\|_M^2}{2l^2}}, \tag{19}$$

where the parameters σ^2 is the variance of the kernel, and l the length scale.
Second, the Rational Quadratic kernel (RQ), the kernel is defined by means of a hyperbolic dependency with the metric,

$$(x, x') = \sigma^2 \left(1 + \frac{\|x-x'\|_M^2}{2\alpha l^2}\right)^{-\alpha}, \tag{20}$$

where the parameters σ^2 is the variance of the kernel, and l the length scale. The parameter α determines the rate at which the kernel diminishes with the metric.

Third, the exponential Kernel (EXP), this is an intermediate kernel in terms of metric decay between the RBF and RatQuad, the formula being as follows

$$k(x, x') = \sigma^2 e^{-\frac{\|x-x'\|_M}{2l^2}}, \tag{21}$$

where the parameters σ^2 is the variance of the kernel, and l the length scale.

Fourth, Matérn Kernel (MAT), this is a family of kernels, that indexed by a parameter that defines the order in which the exponential attenuates with the metric. The distribution is modelled by means of a Bessel function on a isotropic metric dependent on a parameter,ν, for the case of $\nu = ½$ the distribution is reduced to the exponential. Specifically, we will use the distribution for two common cases, $\nu = \{3/3, 5/2\}$, which give rise to the following kernels:

$$k_{3/2}(\mathrm{x}, \mathrm{x}') = \sigma^2 \left(1 + \sqrt{3}\frac{\|x-x'\|_M}{\mathrm{l}}\right) \mathrm{e}^{-\sqrt{3}\frac{\|x-x'\|_M}{l}}, \tag{22}$$

$$k_{5/2}(\mathrm{x}, \mathrm{x}') = \sigma^2 \left(1 + \sqrt{5}\frac{\|x-x'\|_M}{\mathrm{l}} + \frac{5}{3}\frac{\|x-x'\|_M^2}{\mathrm{l}^2}\right) \mathrm{e}^{-\sqrt{5}\frac{\|x-x'\|_M}{l}}, \tag{23}$$

where the parameters σ^2 is the variance of the kernel, and l the length scale.

Fifth, the Multilayer Perceptron Kernel (MLP), this kernel includes a saturating nonlinearity, and the similarity measure between the observations $(\mathrm{x}, \mathrm{x}')$ is based on an affine function of the scalar product between the vectors representing the observations. Unlike the previous kernels, the scalar parameter is defined by the affine relation, $\sigma_w^2 x^\top y + \sigma_b^2$.

$$k(x, \mathrm{x}') = \sigma^2 \frac{2}{\pi} \mathrm{asin}\left(\frac{\sigma_w^2 x^\top \mathrm{x}' + \sigma_b^2}{\sqrt{\sigma_w^2 x^\top x + \sigma_b^2 + 1}\sqrt{\sigma_w^2 \mathrm{x}'^\top \mathrm{x} + \sigma_b^2 + 1}}\right) \tag{24}$$

As in the other kernels, the parameters σ^2 is the variance of the kernel.

Finally, the standard periodic kernel (SP), This is a kernel that models explicitly the periodicity between observations, so there will be in addition to the scale parameter 'l', a term related to the periodicities, which we will denote as 'p'. The structure of

the kernel in the form of an exponential of a trigonometric function, takes into account not only the possible periodicity, but also models the decreasing distance-related relationship between the samples.

$$k(x,x') = \sigma^2 e^{-\frac{2}{l^2}\sin^2\left(\pi\frac{\|x-x'\|_M}{p}\right)} \tag{25}$$

4.5. Combination of kernels

The linear combination of kernels is carried out by the simple sum N of kernels,

$$k_{Total}(x,x') = \sum_{i=1}^{N} k_i(x,x') \tag{26}$$

The weights of the linear combination are given by a σ_i^2 parameter specific for each kernel, which is estimated independently for each of the $k_i(x,x')$, components of the combination $k_{Total}(x,x')$. Note that when maximizing $\hat{\theta} = argmax_\theta\big(p(y \mid X,\theta)\big)$, all the parameters of $\sum_{i=1}^{N} k_i(x,x')$ are adjusted simultaneously. Therefore, in addition to the relative weight of each kernel (determined by the individualσ_i^2), the scale parameter 'l_i ' is adjusted. By adjusting independently each scale parameter the interactions between elements at different scales to be modelled for each kernel separately.

Since parameter optimization is performed by gradient search, the nonlinearity of the kernels results in a multimodal objective function. In order to solve the problem of local minima, different initializations and optimizations were performed in the training, selecting as the final model the one that provided the best performance in validation.

4.6. Selection of the best set of kernels

In this subsection we will describe how the kernels have been selected for the experiments. The description and details of the 7 kernel types used are summarised in the previous list (18-25). There is a total of 127 possible combinations (2^7–1=127). Note that the empty set combination does not count. The method for selecting the kernels was to test all 127 combinations, with multi-starting of 10 repetitions, and selecting the mean value of the MSE and calculating the standard deviation.

The results for selecting the best combination of kernels were obtained by training with 75% of the database partition allocated for training and validating with the final 25% of this partition[7]. A methodological point to note is the difficulty of computing confidence intervals when the data structure is sequential. Note that it makes little sense to sample independent samples to compute the standard deviation, or to select consecutive sub-intervals for training and validation without overlap[8].

4.7. Preprocessing of the data and discussion on kernel selection

Before the forecast, the input data is standardized, i.e., given an input vector $x \in \mathbb{R}^n$, we compute the mean and variance of each feature of x and we normalize each coordinate by $x_i^{nor} = \frac{x_i - m_i}{s_i}$ by subtracting the sample mean m_i and sample variance s_i, each computed over the training database[9].

Finally, the winning combination is the kernel consisting of the sum of three {MLP, RQ, EXP}, so that, the mathematical expression is the following,

$$k(x,x') = k_{MLP}(x,x') + k_{EXP}(x,x') + k_{RQ} \tag{27}$$

This proposed approach allows to preserve the stochastic properties of the training series in multiple-step ahead prediction. In spite of the desirable properties of GPR models, to our knowledge this is the first study to use GPR for causal estimation within the NKPC, and to estimate confidence intervals of the obtained vectorial predictions. This strategy is cost-effective in computational terms, and seems particularly indicated for inflation forecasting.

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[7] The test database was used to evaluate the real performance of the system. In other words, the test base was not used to decide the combination of kernels. Since the problem has a sequential structure, we kept the interval between 2000-01-01 and 2014-03-01 for training, and the interval between, 2014-04-01 to 2018-12-01 for validation. The test interval, defined as the observations between 2019-01-01 and 2021-06-01, was set aside to compute the predictions incrementally in the final results.

[8] Therefore, as a substitute for random sampling, we decided to estimate the standard deviation of each kernel combination by taking the standard deviation of the multi-starting performance. We are aware that we are actually measuring the variability due to the local minima of the cost functions. However, we believe it is a surrogate for variability, which will allow reliable ranking of kernel combinations.

[9] Note that the parameters for normalizing the test database are the ones computed over the training database. Also, when estimating the model, the mean value over the training database is subtracted from the target y, and then added to the forecast on the testing data.

5. Results

To assess the forecasting performance of the proposed extension of the GPR model, we estimate the models and generate forecasts for the forecast horizon *h*=1 month and compute the root mean square forecast error (RMSFE). Forecast accuracy results, together with the estimated values of the hyper parameters are presented in Table 2.

Table 2. Forecast accuracy (RMSFE) of best kernel combination (2019:01–2021:07).

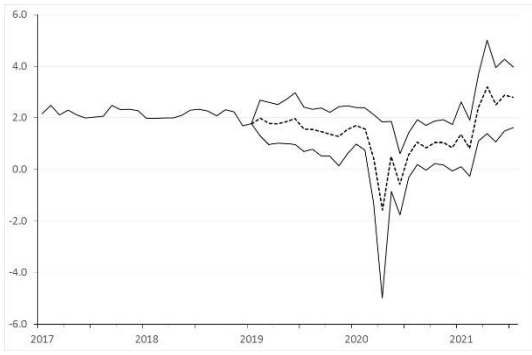
	RMSFE	$k_{MLP}(x,x')$			$k_{EXP}(x,x')$		$k_{RatQuad}(x,x')$		
	h=1	σ^2_{MLP}	σ^2_w	σ^2_b	σ^2_{EXP}	l^2_{EXP}	l^2_{RQ}	l^2_{RQ}	α
Austria	0.253	2.985	0.143	1.161	0.637	2.625	0.148	0.449	0.826
Belgium	0.468	0.592	0.220	0.452	0.389	0.832	1.492	0.383	0.212
Cyprus	0.532	0.535	1.213	1.335	0.278	1.652	0.888	0.639	0.896
Estonia	0.688	0.356	0.217	1.241	1.343	2.400	2.445	1.940	0.596
Finland	0.258	0.443	0.942	0.455	0.270	1.239	0.575	0.977	1.441
France	0.270	0.487	0.688	1.630	0.214	0.952	0.524	0.534	0.249
Germany	0.394	0.447	0.64	0.257	0.307	0.493	0.617	0.717	0.254
Greece	0.623	0.402	0.954	0.845	0.660	0.685	0.289	0.688	0.368
Ireland	0.346	0.462	0.446	1.621	1.471	2.057	0.333	0.332	0.547
Italy	0.357	1.270	0.362	0.596	0.311	0.417	0.249	0.969	0.887
Latvia	0.579	0.560	0.895	0.114	0.376	0.533	2.796	0.697	0.317
Lithuania	0.594	1.075	0.38	1.011	0.673	0.729	1.150	1.044	0.518
Luxemburg	0.604	0.968	0.731	1.709	0.405	0.141	0.592	1.106	0.622
Malta	0.191	0.597	0.831	1.335	0.445	0.502	0.615	1.710	1.160
Netherlands	0.409	0.581	1.720	1.581	0.624	2.099	0.280	0.596	2.534
Portugal	0.439	1.237	0.812	1.184	0.101	0.226	0.101	0.226	0.171
Slovakia	0.331	0.301	0.715	0.787	2.141	1.133	0.396	0.870	0.147
Slovenia	0.528	0.312	1.120	1.189	0.707	0.630	0.953	0.492	0.478
Spain	0.372	1.027	0.678	0.285	0.461	1.367	0.395	0.616	0.180

Notes: Parameter σ^2 is the variance of the kernel, and *l* the length scale. Parameter α determines the rate at which the kernel diminishes with the metric

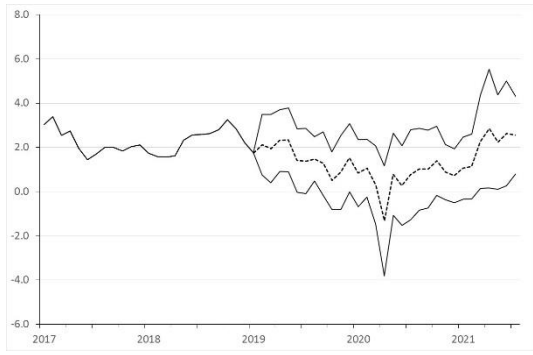
Table 2 shows the overall performance of the assessed forecasting models on all countries. The best forecasting performance is obtained in Malta, Austria, Finland and France. Overall, the proposed GPR model generates low RMSFEs across the examined countries. Our results are comparable to those of [48], who also find that applying GPR substantially benefits the accuracy of inflation forecasting in the US. Our results suggest that the theoretical foundations of the NKPC model provide a good framework for inflation predictions [49].

Figure 2 shows the mean of the density forecasts of inflation for *h*=1 with the 95% confidence intervals obtained with the GPR model for the out-of-sample period. The obtained forecasts reveal the current inflationary pressures [50]. The stated tendencies are mainly caused by the supply chain disruptions due to the pandemic, rising inflationary expectations due to the announcements of an interest rate increase, as well as the recent intensification of aggregate demand after the lockdown policies.

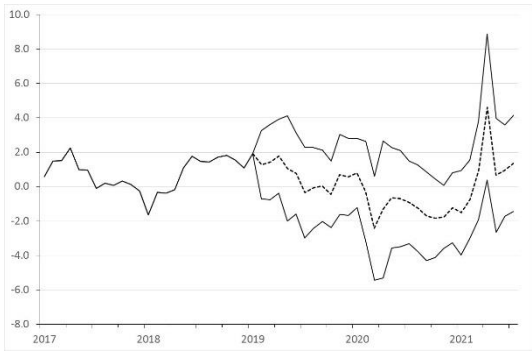
Austria



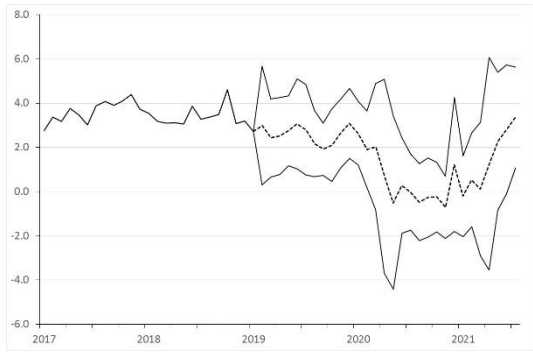
Belgium



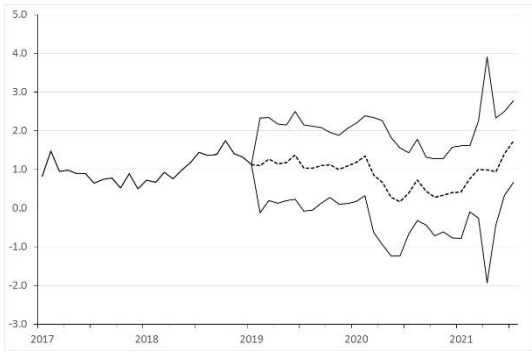
Cyprus



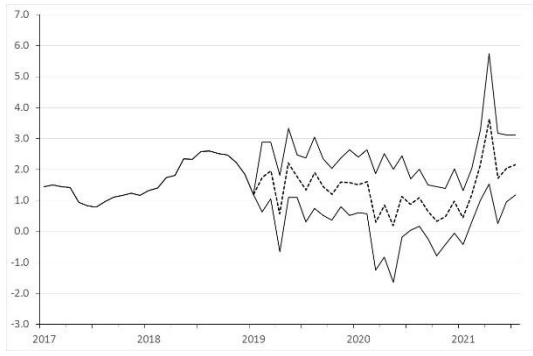
Estonia



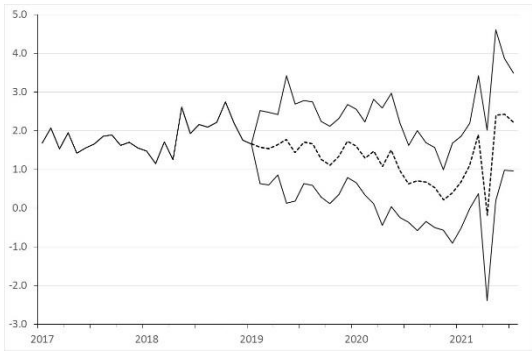
Finland



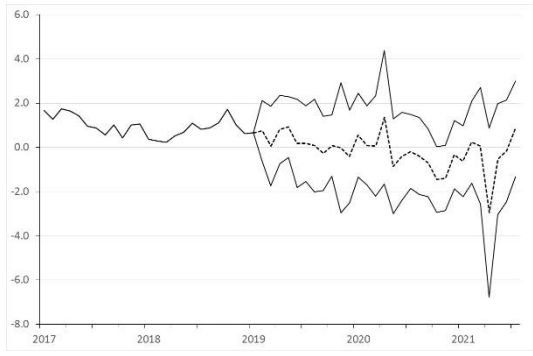
France



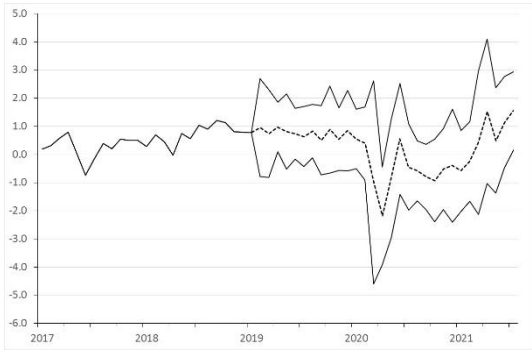
Germany



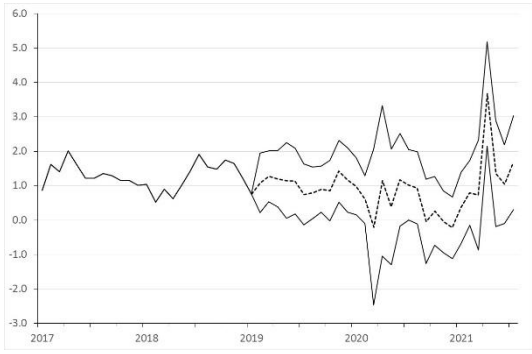
Greece



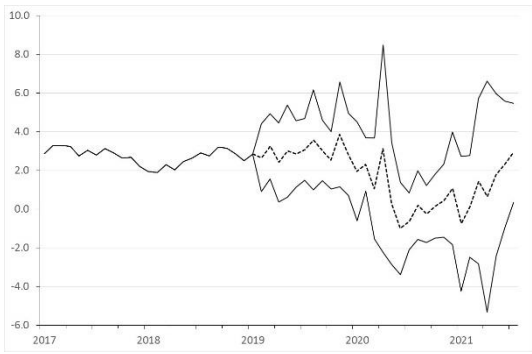
Ireland



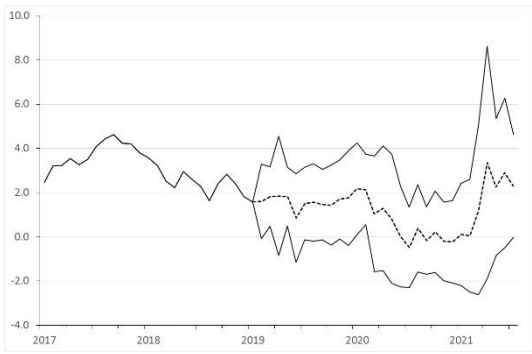
Italy



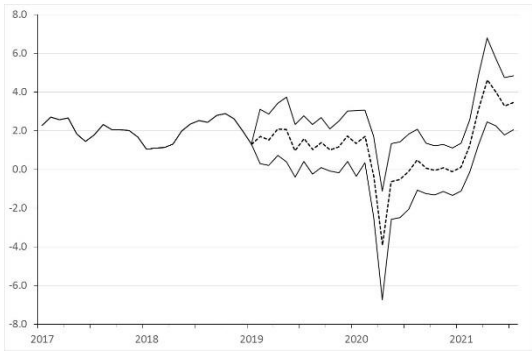
Latvia



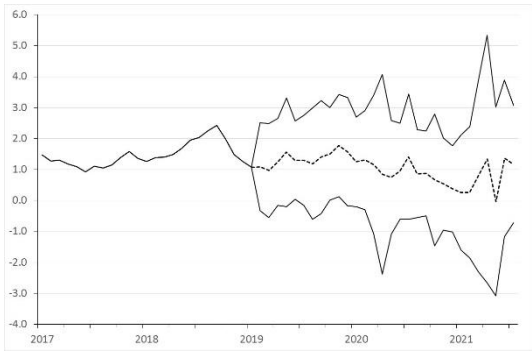
Lithuania



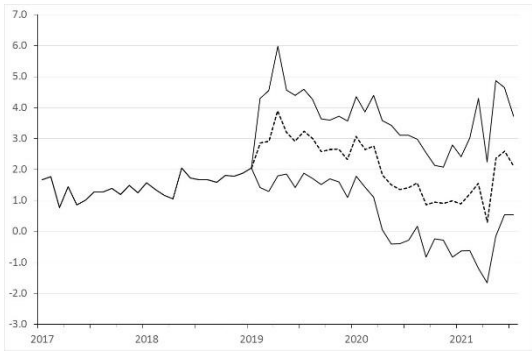
Luxemburg



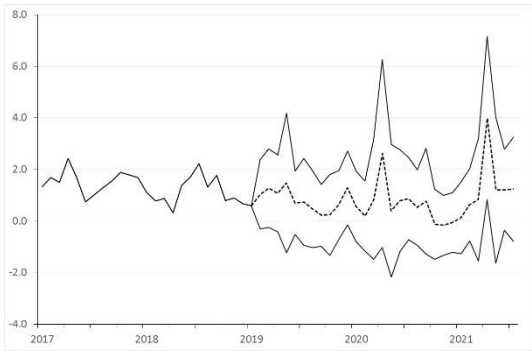
Malta



Netherlands



Portugal



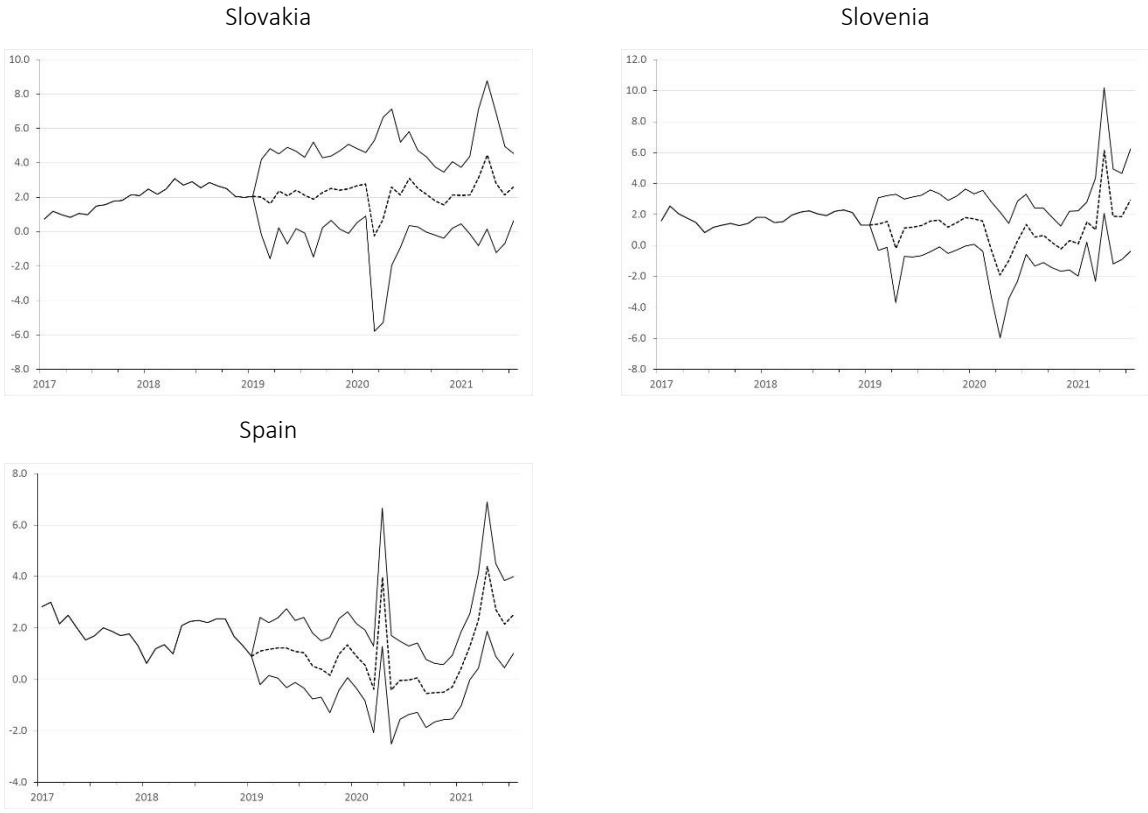


Figure 2. Mean of density forecasts of inflation for *h=1* (2019:01-2021:07). The black-dotted line represents the mean of the density forecasts of inflation for h=1 with confidence intervals obtained with the GPR model for the out-of-sample period (2019:01-2021:07)

6. Concluding Remarks

The current geopolitical tensions, pandemic-related supply chain disruptions and the announcements of rising reference interest rates make the current macroeconomic environment in need of state-of-the-art and accurate inflation forecasting models. Due to the complexity of such a task, we rely on the theoretical NKPC specification as the basis for an adequate choice of model predictors. We contribute to the literature by an initial application of GPR method in forecasting EA inflation. The forecasts obtained within this framework point out the recent inflationary pressures.

Modeling through GPR allows estimating confidence intervals for point forecasts This feature makes forecasting via GPR offer potential in different fields, as it can be used for basically any type of low- or high-frequency economic or financial time series, and any type of theoretical economic model.

As a proposition for future work, research should be done on the potential application of nonparametric specifications of the conditional mean and of the innovation to inflation using GPR, in the vein of Clark et al. [48]. Such a methodological framework, allowing for nonlinearities between inflation and its NKPC-founded determinants, seems as a promising line of research. Further forecasting attempts should also consider potential non-Gaussian properties of inflation dynamics, such as skewness and leptokurtic behaviour.

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Data Availability Statement: The datasets used and/or analysed during the current study are: i) the Joint Harmonised EU Consumer Survey conducted by the European Commission, which can be freely downloaded at https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en, ii) two official macroeconomic time series (monthly industrial production index and Euro area 3-month money market interest rate)—which can be freely available at: https://ec.europa.eu/eurostat/web/main/data/database, and iii) crude oil prices (Brent Europe), freely available at: https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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